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Comparison of Model Validation Techniques for Land Cover Dynamics in Jodhpur City

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Abstract: ***This study investigate comparison of Land cover map to quantify the characteristics of three different land change simulation models. The land change models used for simulation are termed as Stochastic Markov (St_Markov), Cellular Automata Markov (CA_Markov) and Multi Layer Perceptron Markov (MLP_Markov) models. It is found that MLP Markov gives the best results among the three modeling techniques. After simulating the land cover dynamics, various model validation techniques such as per category method, kappa statistics and fuzzy methods have been used. A comparative study of the validation techniques has also been analyze. Fuzzy set theory is the method that seems best able to distinguish areas of minor spatial errors from major spatial errors. Based on the output results, it is recommended to use the Kappa, map comparison and fuzzy methods for model validation process. This study demonstrates the range of results for a variety of model validation techniques which can be use for future research.***

Keywords: Validation, Fuzzy Kappa, MLP_Markov

1. INTRODUCTION

The evaluation of spatial similarities and land use change between two raster maps is traditionally based on pixel-by-pixel comparison techniques. This kind of change detection procedure is called the post-classification comparisons. different methods have been introduced and new software packages are being developed, for the sake of map comparison/validation of models that predict land cover change from a map of initial time to a map of a subsequent time. The main purpose of this study is to find out whether the simulation is giving any abrupt result or not and to compare among the different model validation techniques. Study also shows the advantages and disadvantages of commonly-used map comparison techniques to assess the agreement between the simulated maps and the actual land-cover maps.

2. STUDY AREA

Jodhpur is centrally situated in western region of the Rajasthan state. Jodhpur city is located at 26ºN 18' latitude and 73º E 04' and at an average altitude of 224m above mean sea level. In general, the contours are falling from North to South and from North to Southeast with maximum level of 370m and minimum of 210m. The present population is about 1.05 million and admeasures 230sq.km. Jodhpur has strategic positioning apart from its close proximity to the state capital Jaipur. The establishment of large-scale core industries has led to the growth of ancillary and small-scale industries in and around this industrial belt (Fig.1).

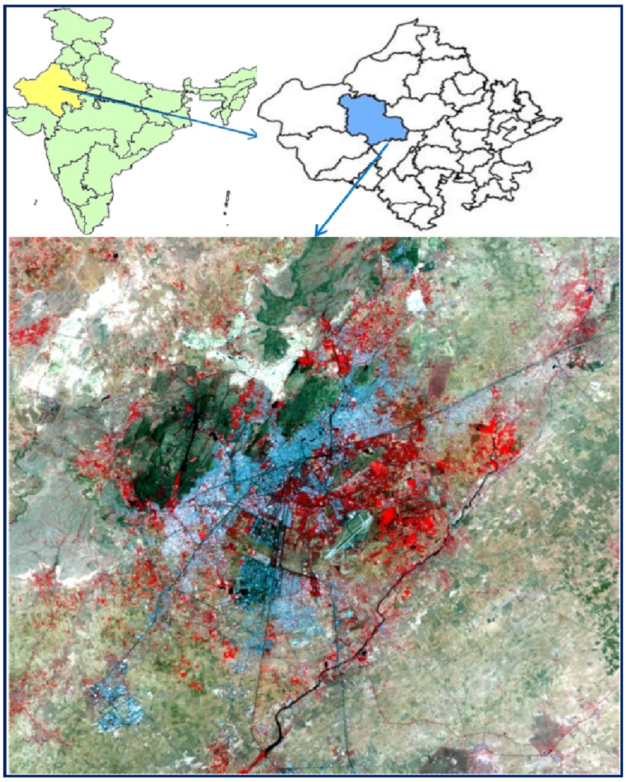

Figure 1 Location Map of the Study Area.

3. DATASET USED AND METHODOLOGY

To prepare the Land cover maps of the study area, the Landsat satellite images (1990, 2000 and 2010) have been used (Table-1). SoI maps, ground truth data were used for land use classification and accuracy analysis. Supervised classification method applied to prepare the Land cover maps. ArcGIS and ERDAS Imagine software were used to achieve land use classification mapping in a multi-temporal approach. Five land use types i.e. built -up area, vegetation, mining area, waterbody and other area have been identified in this study. For simulation of land use change, Three modelling method as St_Markov, CA_Markov and MLP_Markov Model have been used for modelling of land dynamics. IDRISI Selva software with Land Change Modeler used in this paper for analysis of land use changes. Different model validation techniques are also used to validate the simulated land cover change i.e. the Kappa, map comparison and fuzzy methods.

Table 1. Basic Properties of Landsat Data

Acquisition Date	Landsat Sensor	Spatial Resolution	Number of Bands
Oct - 1990	LANDSAT TM	30m	7
Oct - 2000	LANDSAT ETM	3m	8
Oct - 2010	LANDSAT ETM	30m	8

4. RESULT AND DISCUSSION

Initially accuracy assessment of temporal land cover classification maps, simulation of land cover change for 2010 carried out to generate prediction maps. The comparisons between the actual land use (base) map (2010) and the simulated maps (St_Markov, CA_Markov and MLP_Markov) of year 2010 have been achieved. The main aim of model validation is to find out whether the simulation is giving any unexpected result or not. Statistical approach has been used for validating the simulated maps. This approach explains the situation in a quantitative way.

4.1 Prediction of Land Cover Maps

The IDRISI Selva software is used for modelling land cover changes in Jodhpur city. First method is Stochastic Markov Model that has been implemented is given the name as (St_Markov), because this model combines both the Stochastic processes as well Markov Chain analysis techniques. The second method is Cellular Automata Markov Model (CA_Markov), combines the concepts of Markov Chain and Cellular Automata. The third model is Multi Layer Perceptron Markov Model (MLP_Markov). MLP_Markov combines the concepts of Markov Chain, Artificial Neural Network. The St_Markov, CA_Markov and MLP_Marko methods have been adopted from Ahmed and Ahmed (2012). The simulation result of land cover change are shown in Fig.2.

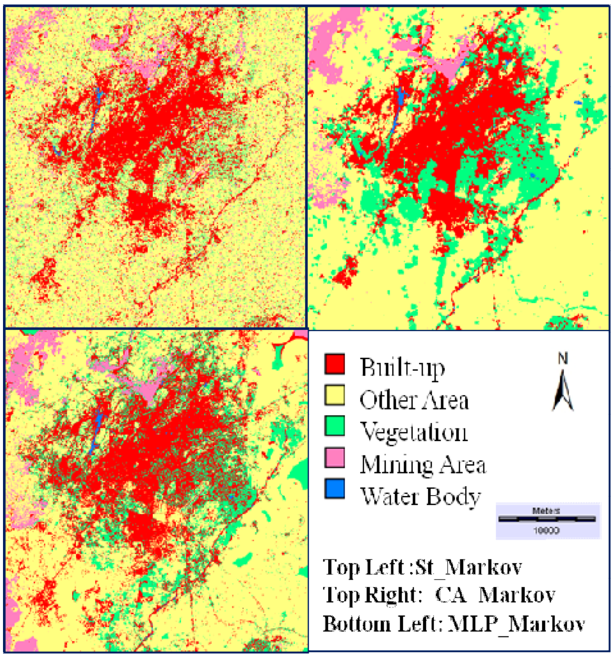

Figure 2 Predicted land cover maps of Jodhpur City (2010).

4.2 Per Category Method

The per category comparison method is a cell-by-cell comparison with respect to selected land cover category. It concurrently gives the user information about the occurrence of the selected category in both maps. Figure(3,4 &5) show the method that carry out cell-by-cell comparison for each land cover class. The outputs are depicted in four different legends indication different states of comparison. The more there will be the amount of both maps, the better the simulation result. Combinations (Base Map 2010 vs. St_Markov 2010, Base Map 2010 vs. CA_Markov 2010 and Base Map 2010 vs. MLP_Markov 2010) are taken into consideration. It is then found that the simulated map of MLP_Markov 2010 shows the best results for all the land cover categories in terms of the highest amount of the legend in both maps. The class 'in both maps' is higher in case of built-up area. It means the agreement in cells for built-up area is quite good. On the other hand, there is no sign of the class 'in both maps' in water body. This means there is no agreement in water body. In case of vegetation and mining area the agreement among cells seems moderate. Other area shows high amount of only in map 2 but not in map 1 and only in map 1 and not in map 2 classes. It means low degree of agreement exists in other area. The more amount of both maps there will be the better simulation result. Three statistics are compared in each confusion matrix: overall accuracy, producer's accuracy, and user's accuracy. The kappa coefficients of per category for the three modullation method are showing proves the level of agreement is almost perfect (Table 2,3&4).

Table 2: Per Category Kappa Statistics(St_Markov)

	Built-up	Other Area	Vegetation	Mining Area	Water Body
Kappa	0.921	0.540	0.270	0.393	0.373
KLocation	0.983	0.549	0.318	0.474	0.452
KHisto	0.921	0.985	0.848	0.829	0.824

Table-3: Per Category Kappa Statistics (CA_Markov)

	Built -up	Other Area	Vegetation	Mining Area	Water Body
Kappa	0.831	0.768	0.575	0.882	0.846
KLocation	0.852	0.805	0.632	0.963	0.952
KHisto	0.976	0.954	0.910	0.941	0.889

Pontius (2000, 2002) proved that standard Kappa (Cohen's Kappa) offers nearly no useful information because it confounds quantification error with location error. Therefore, four kappa statistics are presented here the traditional kappa (Kstandard), a revised general kappa defined as kappa for no ability (Kno), and two other detailed kappa statistics to differentiate accuracies in quantity and location (Kquantity and Klocation). The Kno statistic is an improved general statistic over Kstandard as it penalizes large quantity errors and rewards further correct location classifications, while Kquantity and Klocation are able to distinguish clearly between quantification error and location error, respectively. After analyzing Table-5, it can be concluded that MLP_Markov is showing the highest values of kappa coefficients among the three models. The assumption is like the higher the kappa values, the better the model.

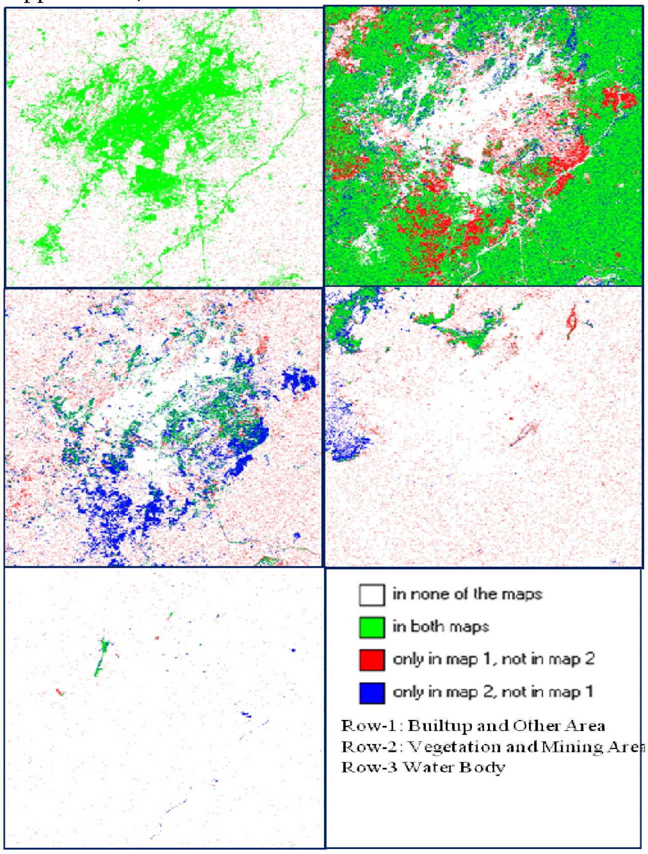

Figure 3 Per Category Comparison Method (Base Map 2010 vs. St_Markov2010)

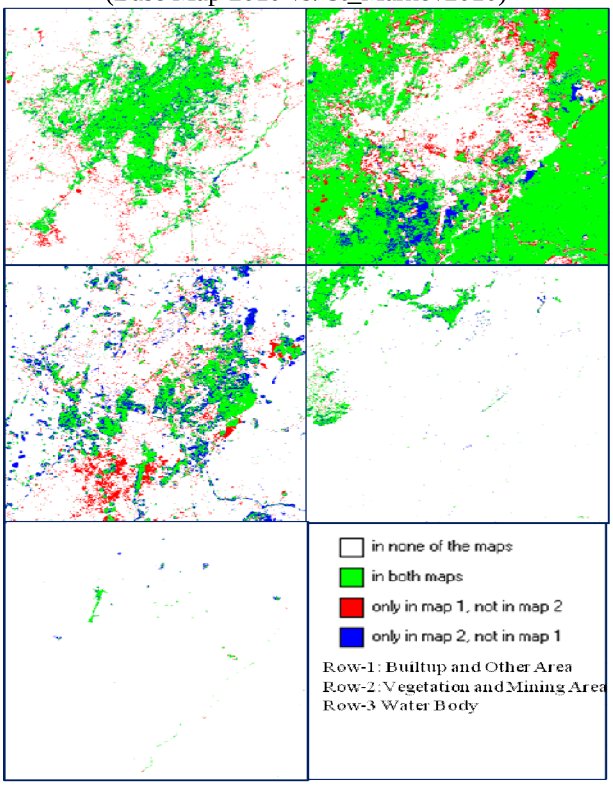

Figure 4 Per Category Comparison Method (Base Map 2010 vs. CA_Markov2010)

Table-4: Per Category Kappa Statistics(MLP_Markov)

	Built-up	Other Area	Vegetation	Mining Area	Water Body
Kappa	0.856	0.798	0.754	0.882	0.935
K Location	1.000	0.901	0.772	1.000	0.979
K Histo	0.856	0.981	0.985	0.952	0.956

Table 5 Overall Kappa Statistics and Fraction Correct

	St_Markov (2010)	**CA_Markov (2010)**	**MLP_Markov (2010)**
FractionCorrect	0.767	0.858	0.886
K location	0.632	0.791	0.858
K histo	0.925	0.948	0.950
Kappa	0.584	0.750	0.770

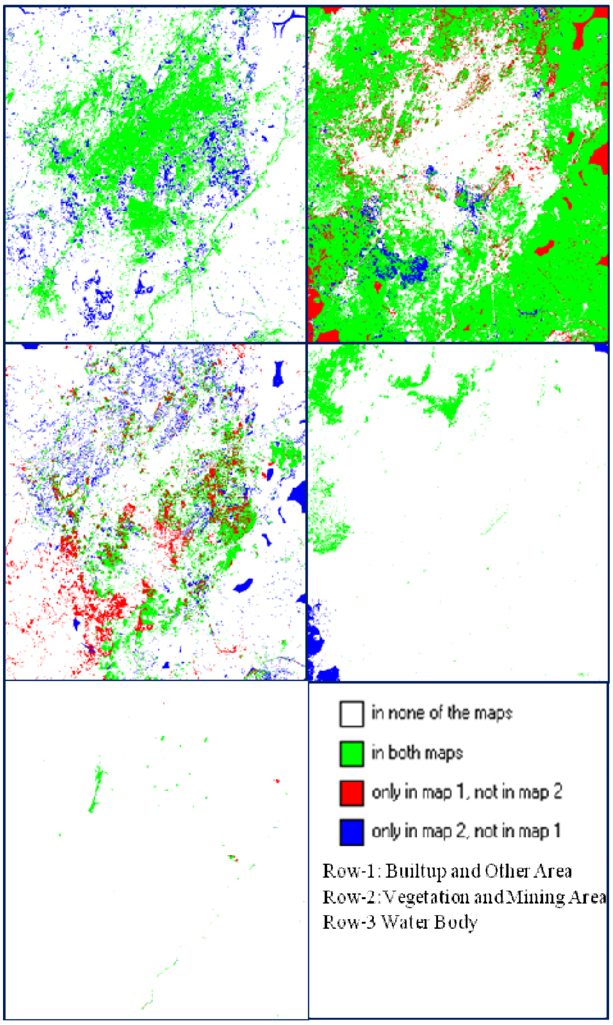

Figure 5 Per Category Comparison Method. (Base Map 2010 vs. MLP_Markov2010)

4.3 Fuzzy Kappa Analysis

Fuzzy kappa map comparison shows the grades of similarity between pairs of cells. The main difference with the cell-by-cell map comparison is that fuzzy kappa map comparison takes into account the neighbourhood of a cell. Then it represents the cell values between 0.00 (fully distinct) to 1.0 (fully identical). The statistic of fuzzy kappa is similar to Kappa. The main difference lies in the calculation of the expected similarity. The fuzzy cell-by-cell method is used for comparing each of the three different simulations with the base map of 2010 (Fig.6) . The fuzzy membership function is that of exponential decay with a halving distance of two cells and a neighborhood with a four cell radius. Later the fuzzy output maps have been categorized into three levels of agreement: equal and unequal. Both fuzzy Kappa and average similarity is found highest for MLP_Markov and lowest for St_Markov‖ model (Table-6).

Table 6 Agreements of fuzzy Similarity for Validation.

Modeling	Fuzzy Kappa	Average Similarity
St_Markov	0.401	0.731
CA_Markov	0.794	0.887
MLP_Markov	0.906	0.918

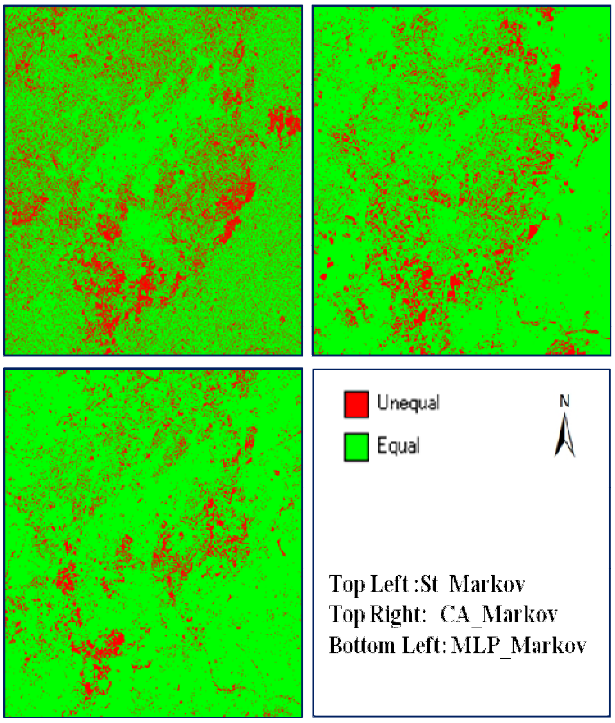

Figure 6 Levels of Agreement for Kappa.

5. CONCLUSION

Three models are implemented to simulate the land cover maps of Jodhpur City with base map of 2010. Models used are Stochastic Markov (St_Markov), Cellular Automata Markov (CA_Markov) and Multi Layer Perceptron Markov (MLP_Markov) model. Different model validation techniques like per category method, kappa statistics, map comparison and fuzzy method are used. Fuzzy set theory is found best able to distinguish areas of minor spatial errors from major spatial errors. In all cases, it is found that MLP_Markov is giving the best results among the three modeling techniques.

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